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AN APPLICATION OF ARTIFICIAL INTELLIGENCE THEORY TO RECONFIGURABLE FLIGHT CONTROL

David A. Handelman
Princeton University
Princeton, New Jersey

THE NEED FOR INTELLIGENT FLIGHT CONTROL

Many fatal aircraft accidents appear to be the result of a misuse of information, knowledge, or capability. For instance, a pilot depends on instruments for accurate aircraft status information. Inaccurate or partial information deprives the pilot of the resources necessary to safely operate the aircraft, and thus constitutes a misuse of information. Similarly, negligence or inexperience on the part of the pilot represents a misuse of knowledge. Finally, modern generic jet aircraft have highly redundant control effectors. As a result, it may be possible to counterbalance the effect of a failed primary control effector, such as an aileron, with a secondary control effector, such as a trailing-edge flap. If an aircraft is controllable following a failure, but through a lack of information, knowledge, or ability the pilot fails to control it, this represents a misuse of capability.

FATAL ACCIDENTS OF U.S. SCHEDULED AIR CARRIERS, 1961-1979

- Reverse thrust warning light malfunction
- Landing gear warning light malfunction
- Loss of electrical system to attitude instruments

- Turbulence, airframe failure in flight
- Hydraulic pressure loss uncorrected by pilot

- Hydraulic system degradation
- Rudder support material failure
- Rudder control system malfunction
- Flight control system failure
- Failure of engine pylon

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RESEARCH OBJECTIVES

The objective of this research is to use artificial intelligence techniques, along with statistical hypothesis testing and modern control theory, to help the pilot cope with the issues of information, knowledge, and capability in the event of a failure. We are developing an "intelligent" flight control system which utilizes knowledge of cause-and-effect relationships between all aircraft components. It will screen the information available to the pilot, supplement his knowledge, and most importantly, utilize the remaining flight capability of the aircraft following a failure. The list of failure types the control system will accommodate includes sensor failures, actuator failures, and structural failures.

PURPOSE

- TO INVESTIGATE THE POSSIBLE CONTRIBUTION OF ARTIFICIAL INTELLIGENCE TECHNIQUES TO AIRCRAFT FAILURE DETECTION, IDENTIFICATION, AND RECONFIGURATION (FDIR)

MOTIVATION

- MOST EXISTING FDIR SCHEMES CAN HANDLE ONLY A SUBSET OF ALL POSSIBLE AIRCRAFT FAILURES

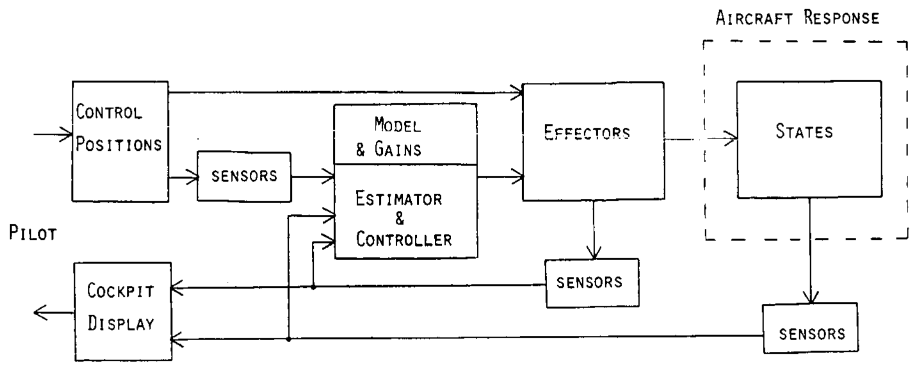
- FEW EXISTING FDIR SCHEMES INCORPORATE HUMAN-LIKE COMMON SENSE OR KNOWLEDGE RELATING ALL AIRCRAFT COMPONENTS

- REDUNDANCY IN MODERN AIRCRAFT MAY PERMIT RECOVERY FROM SEVERE FAILURES

ASSUMPTIONS

In order to adapt to significant failure-induced changes in the configuration of the aircraft, the control system must have a variable structure. A fly-by-wire flight control system can be reconfigured by supplying new mathematical models and gains to the computer, thus a control system of this form is assumed. Note that the pilot flies the aircraft via the flight computer and has no direct link to the control surfaces. It is essential, therefore, that the flight computer have the model and gains corresponding to the actual aircraft configuration. Assuming that a failure will significantly change the configuration, it will be the job of the knowledge-based reconfigurable flight control system (KBRFCS) to replace the pre-failure model with the correct model.

BASIC FLY-BY-WIRE FLIGHT CONTROL SYSTEM



STATE - SPACE MODEL

$$\underline{x}(k+1) = \Phi(k)\underline{x}(k) + \Gamma(k)\underline{u}(k) + \underline{g}(k) + \underline{w}(k)$$
$$\underline{y}(k) = H_x(k)\underline{x}(k) + H_u(k)\underline{u}(k) + \underline{b}(k) + \underline{v}(k)$$

$\underline{g}(k)$, $\underline{b}(k)$ = DETERMINISTIC BIASES

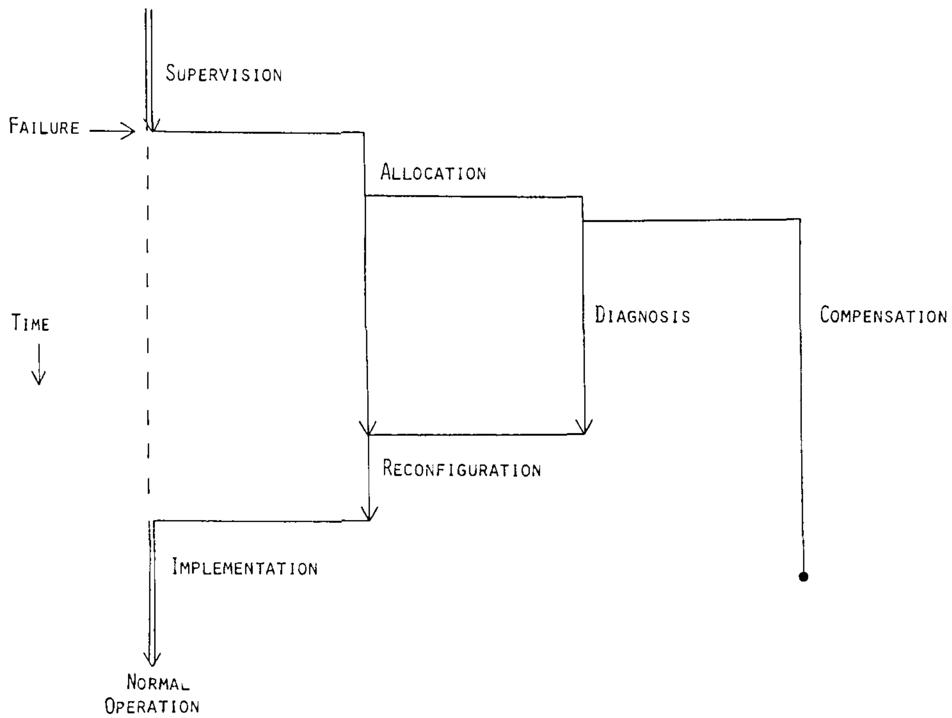
$\underline{w}(k)$, $\underline{v}(k)$ = INDEPENDENT, ZERO-MEAN GAUSSIAN WHITE NOISE PROCESSES

$$E[\underline{w}(k)\underline{w}(j)^T] = Q(k)\delta_{jk}$$

$$E[\underline{v}(k)\underline{v}(j)^T] = R(k)\delta_{jk}$$

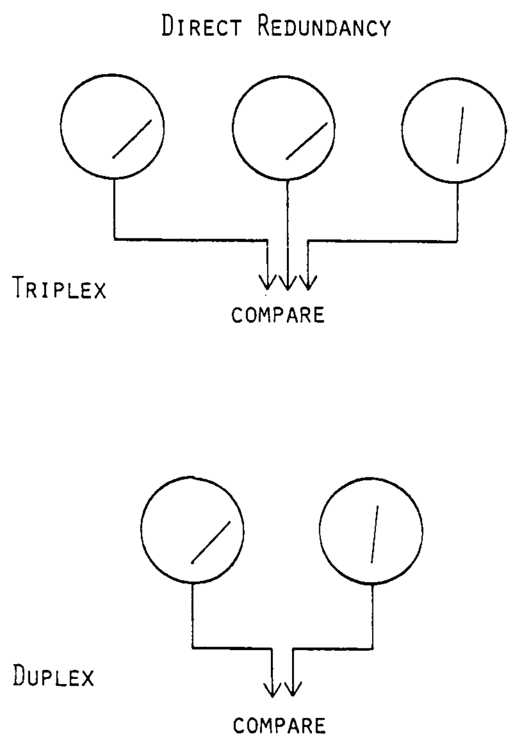
A PROCEDURE FOR INTELLIGENT FAILURE MANAGEMENT

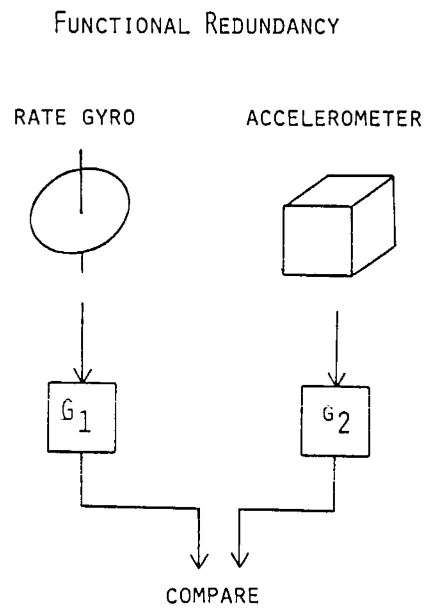
One method of dealing with the problem of failure detection, identification, and reconfiguration (FDIR) is the following. The KBRFCS supervises aircraft behavior until some abnormality occurs, at which time a failure alert is given. The system then allocates its resources to best serve the problem-solving process. This will be important if implementation requires a multi-microprocessor environment. Next, the system tries to diagnose exactly what has failed. Concurrently, immediate and temporary measures are taken to help reduce the effect of the failure during diagnosis. An example of such compensation would be the deflection of a flap to offset a sudden, unexplained roll. When the failure is identified, the best control configuration given the present circumstances is chosen and reconfiguration begins. Finally, the new control scheme is implemented.



FAILURE DETECTION AND DIAGNOSIS PROBLEMS

The easiest way to detect and identify a sensor failure is to compare three sensors which measure the same quantity. Such a triplex system can be very expensive, however. In the less expensive duplex system a failure is easy to detect but hard to identify. Functional redundancy between unique sensors can be exploited to further reduce costs. For example, a rate gyro and an accelerometer can each provide pitch rate information; therefore, the signals can be compared to detect a failure in one of the two components. Although seemingly straightforward, these FDI techniques can run into problems. Consider a triplex system in which two of the sensors are powered from one electrical source and the third sensor from a different source. If the triplex FDI scheme identified a failure by singling out the one sensor which differed from the other two, a power failure to the first two sensors would be misconstrued as a failure of the third. This brings up the need for the incorporation of intelligence into the failure diagnosis process, an intelligence which will recognize when such "higher-order" relations among different elements of the aircraft exist.





SOME EXISTING FAILURE DETECTION AND DIAGNOSIS SOLUTIONS

When the attempt is made to detect and diagnose all types of failures, not simply sensor failures, it is necessary to use all the analytical redundancy available. The generalized likelihood ratio (GLR) method and the multiple model (MM) method are two algorithms which use this redundancy to choose, from a finite set of alternatives, the mathematical model which best predicts the actual aircraft behavior. In FDI the set of alternatives would be the set of failures one hopes to detect and identify. The GLR method is well suited to failure detection, while the MM method is more effective at failure identification. Therefore, one way to accomplish FDIR would be to first detect a failure with the GLR, then run the MM algorithm to choose the proper model from the set of all possible failure models.

GENERALIZED LIKELIHOOD RATIO (GLR) METHOD

BASIS

DIFFERENT ABRUPT CHANGES PRODUCE DIFFERENT EFFECTS ON FILTER INNOVATIONS

ADVANTAGES

- LIKELIHOOD CALCULATIONS BASED ON SINGLE NOMINAL KALMAN FILTER
- WITH MAGNITUDE OF FAILURE KNOWN, SIMPLIFIED GLR (SGLR) RESULTS IN VERY LOW COMPUTATIONAL LOAD
- EFFECTIVELY DETECTS ABRUPT CHANGES

DISADVANTAGES

- ACCOMMODATES ADDITIVE EFFECTS ON SINGLE NOMINAL MODEL ONLY

MULTIPLE MODEL (MM) METHOD

OPERATION

- OBSERVE U(K) AND Y(K)
- CHOOSE MOST LIKELY MODEL FROM FINITE SET OF HYPOTHESES
- RECURSIVE PROBABILITY FORMULA FROM BAYES' RULE

ADVANTAGES

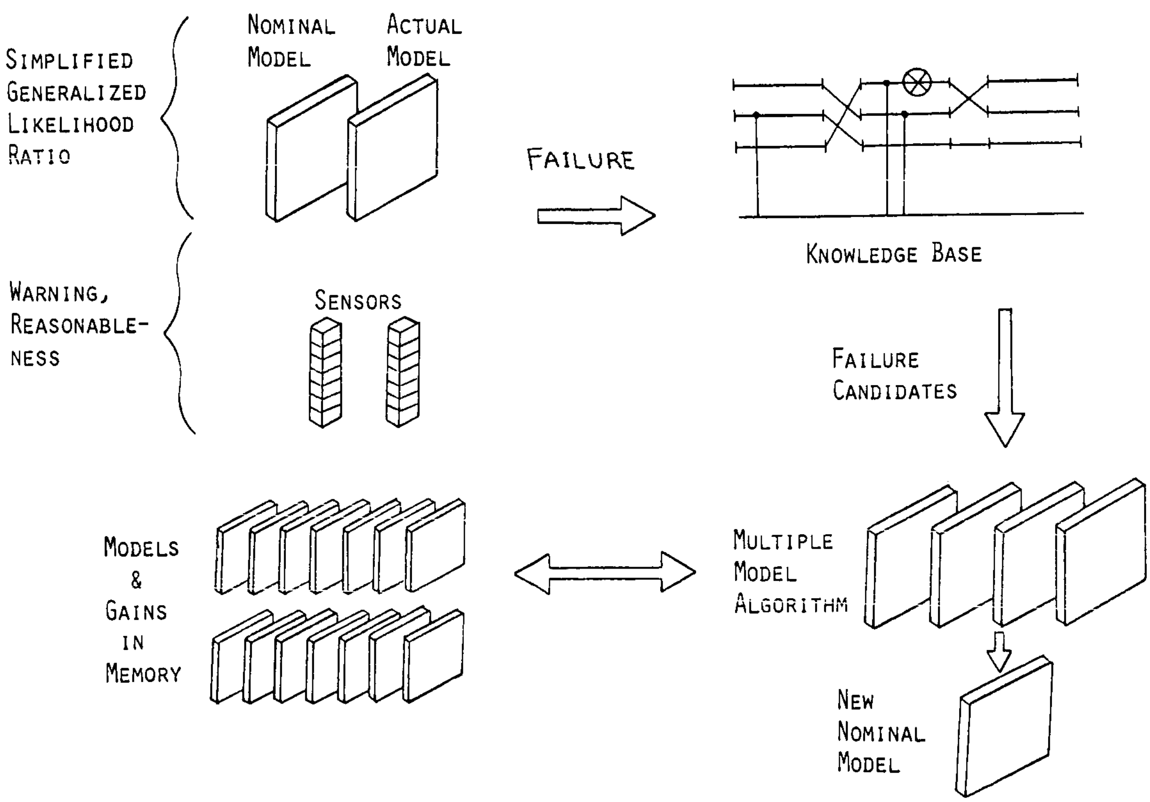
- ALLOWS PARAMETRIC AS WELL AS ADDITIVE CHANGES
- COMPARES MODELS OF DIFFERENT ORDER
- ROBUST TO NON-GAUSSIAN STATISTICS

DISADVANTAGES

- HIGH COMPUTATIONAL BURDEN
- BANK OF KALMAN FILTERS
- SWITCH DETECTION REQUIRES GROWING NUMBER OF FILTERS
- SLOW RESPONSE TO MODEL SWITCHES

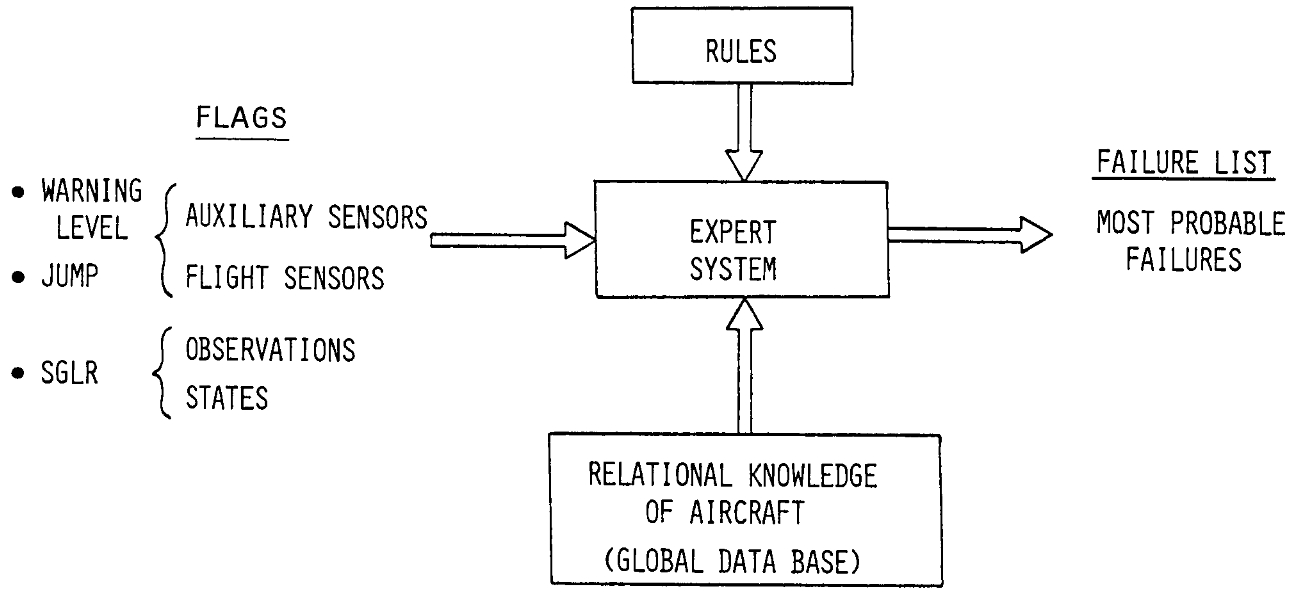
AN ALTERNATE SOLUTION

The KBRFCS will be expected to handle many types of failures. Each failure will change the aircraft configuration in a unique way and will therefore have a unique model associated with it. If the previously mentioned FDIR scheme is employed, the MM algorithm will be required to choose from among thousands of models. Although this may be a theoretically feasible solution, it will require an immense amount of computing power. Our goals include eventual implementation and flight testing of the control system, and computer resources must be kept to a minimum. If there was a way to let the MM algorithm test only those models corresponding to failures which are most likely under the circumstances, the required computer speed could be drastically reduced. In the KBRFCS, this important diagnostic tool takes the form of an expert system.



THE EXPERT SYSTEM

The job of the expert system is to narrow down to a reasonable number the list of possible failures to be tested by the MM algorithm. When a sensor value goes beyond a prespecified warning level, or if it jumps too quickly, or if a state or observation bias jump is picked up by the GLR, a failure is detected and this information is passed on to the expert system. With knowledge of the cause-and-effect relationships among all aircraft components and common-sense failure diagnosis rules, the expert system decides which failures are most likely to have occurred.



THE GLOBAL DATA BASE AND THE RULES

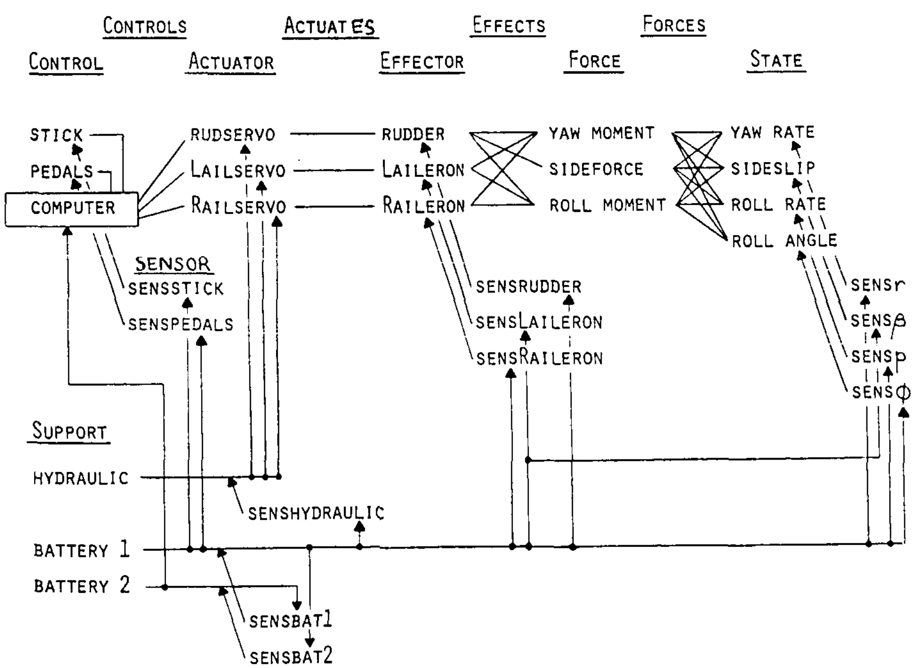
The aircraft relational knowledge is contained in the global data base. The rules combine this knowledge with heuristic, common-sense reasoning to diagnose a failure. The following example illustrates the type of rules the expert system contains.

Rule #1 — If a sensor (such as an aileron position sensor) has exceeded its expected value and that sensor senses an effector (such as an aileron) and no states (including roll rate) have exceeded their expected values then - a sensor failure is likely and an electrical support (for that sensor) failure is likely.

Rule #2 — If a sensor has exceeded its expected value and that sensor senses an effector and that effector strongly effects a state which has exceeded its expected value then - an effector failure is likely.

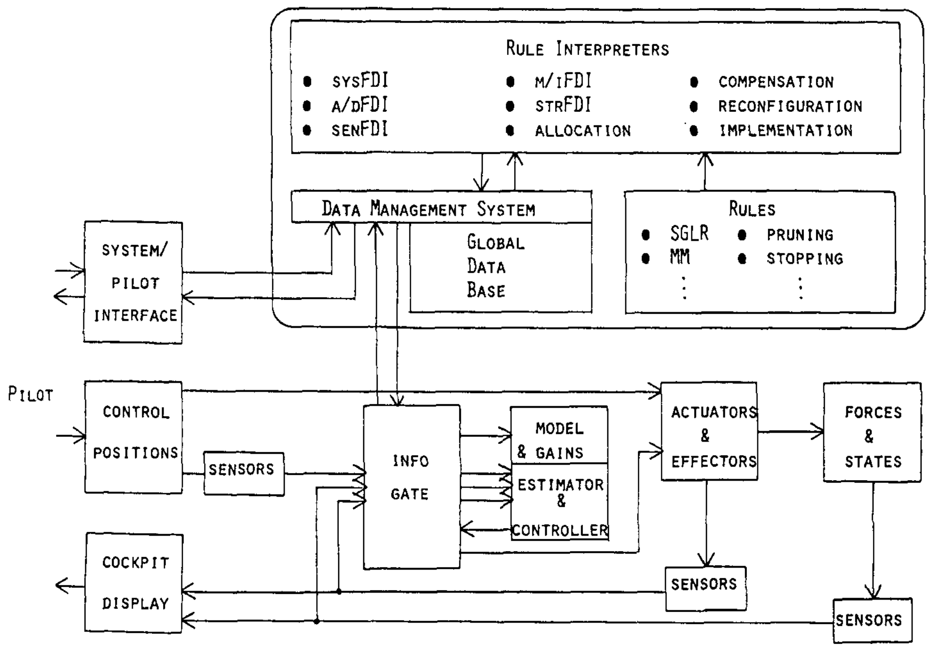
These rules show how the expert system can distinguish between a failed effector which is sensed and a failed sensor.

KBRFCS GLOBAL DATA BASE



KNOWLEDGE-BASED RECONFIGURABLE FLIGHT CONTROL SYSTEM

Although the expert system contains many rules, only a small number of them will be pertinent to a given failure at a given point in the diagnostic process. For example, if a failure is detected and no state bias jumps were observed by the GLR test, the expert system should not waste time testing rules which depend on the existence of a state bias jump in order to be true. The "rule interpreters" provide the control structure needed to select the appropriate rules to be tested. With the expert system complete, the KBRFCS becomes an intelligent and valuable mechanism capable of accommodating failures that a pilot may not be able to handle alone.



RESEARCH WORK SCHEDULE

- Theoretical development
- Nominal Model Selection
- Failure set generation
- Gain calculation
- Knowledge generation through GLR, SGLR, and MM testing
- General rule development
- Global data base development
- Specific rule development
- Rule interpreter development
- Multi-microprocessor simulation